
Self-Training with Dynamic Weighting for Robust Gradual Domain Adaptation

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Abstract

In this paper, we propose a new method called *Self-Training with Dynamic Weighting* (STDW), which aims to enhance robustness in Gradual Domain Adaptation (GDA) by addressing the challenge of smooth knowledge migration from the source to the target domain. Traditional GDA methods mitigate domain shift through intermediate domains and self-training but often suffer from inefficient knowledge migration or incomplete intermediate data. Our approach introduces a dynamic weighting mechanism that adaptively balances the loss contributions of the source and target domains during training. Specifically, we design an optimization framework governed by a time-varying hyperparameter ϱ (progressing from 0 to 1), which controls the strength of domain-specific learning and ensures stable adaptation. The method leverages self-training to generate pseudo-labels and optimizes a weighted objective function for iterative model updates, maintaining robustness across intermediate domains. Experiments on rotated MNIST, color-shifted MNIST, portrait datasets, and the Cover Type dataset demonstrate that STDW outperforms existing baselines. Ablation studies further validate the critical role of ϱ 's dynamic scheduling in achieving progressive adaptation, confirming its effectiveness in reducing domain bias and improving generalization. This work provides both theoretical insights and a practical framework for robust gradual domain adaptation, with potential applications in dynamic real-world scenarios. The code is available at <https://github.com/Dramwig/STDW>.

1 Introduction

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The phenomenon of domain shift presents a fundamental challenge in machine learning systems, where the statistical properties of training (source) and deployment (target) domains exhibit significant divergence [1, 2]. As illustrated in Figure 1, this distributional mismatch frequently arises in practical applications where target domain annotations are either prohibitively expensive or fundamentally unavailable. Domain adaptation (DA) methodologies [3, 4] have emerged as a critical paradigm for addressing this challenge, particularly through the framework of unsupervised domain adaptation (UDA) [5]. However, conventional UDA approaches demonstrate limited efficacy when confronted with substantial domain discrepancies or when transitional domain data is sparse or absent.

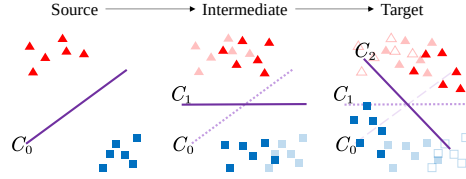


Figure 1: Overview of gradual domain adaptation. The classifiers perform accurately in classifying the sample points in the current domain and the neighboring domains, but fail when classifying the samples from the Source directly to the Target domain.

Recent theoretical and empirical advances have established Gradual Domain Adaptation (GDA) as a promising alternative for mitigating these limitations. The GDA framework, as formalized by [6] and extended by [7], implements a sequential knowledge migration mechanism that systematically reduces the inter-domain discrepancy through intermediate transitional phases. Although this paradigm demonstrates improved stability compared to direct adaptation approaches [8], current GDA implementations exhibit inefficient information flow between adjacent domains, resulting in gradual performance degradation throughout the adaptation trajectory [9]. Moreover, the sequential nature of GDA introduces compounding approximation errors, particularly when transitioning through numerous intermediate domains [10].

This paper proposed *Self-Training with Dynamic Weighting* (STDW), identify and address three critical challenges in existing GDA approaches: (1) suboptimal knowledge propagation across domains, (2) instability during transitional phases, and (3) limited generalization capability. Our STDW introduces a principled framework that fundamentally rethinks the domain adaptation paradigm through two key innovations:

- A theoretically-grounded optimization framework employing the time-dependent parameter $\varrho \in [0, 1]$, which orchestrates a smooth transition from source to target domain representation learning. This mechanism ensures controlled knowledge assimilation while maintaining model stability throughout the adaptation trajectory.
- An integrated self-training paradigm that synergistically combines pseudo-label refinement with adaptive loss reweighting, effectively addressing the domain shift problem through iterative model purification and confidence-aware sample selection.

Through extensive empirical validation across four benchmark datasets - including Rotated MNIST, Color-shifted MNIST, Portrait, and Cover Type datasets - we demonstrate that STDW achieves state-of-the-art performance, outperforming existing methods by significant margins. Comprehensive ablation studies further verify the critical role of our dynamic weighting mechanism and its superior ability to facilitate robust knowledge migration across domains. The proposed framework establishes new theoretical foundations for gradual domain adaptation while providing practical insights for real-world applications.

2 Related Work

Domain Generalization (DG) has emerged as a principled approach to address the fundamental challenge of distributional shift without requiring access to target domain data during training [11]. The theoretical underpinnings of DG trace back to kernel-based methods for learning domain-invariant representations, as formalized by [12], who established important connections between feature space alignment and generalization performance. Subsequent developments have significantly expanded this paradigm through adversarial learning frameworks that explicitly minimize the discriminability of domain-specific features while preserving task-relevant information [13]. A parallel line of research has demonstrated the effectiveness of data-centric approaches in simulating domain variations during training. The work of [14] pioneered sophisticated data augmentation strategies that generate synthetic

domain shifts through carefully designed transformations, effectively creating a continuum of virtual training environments.

More recently, the field has witnessed significant advances through the integration of meta-learning principles into the DG framework. [15] and [16] have reformulated the problem as a meta-optimization task, where models are trained to rapidly adapt to simulated domain shifts presented in episodic training scenarios. This meta-learning perspective provides formal generalization guarantees and has established new state-of-the-art performance across multiple benchmark datasets. While these approaches demonstrate impressive results in controlled evaluations, our analysis reveals persistent limitations when confronting substantial domain discrepancies, particularly in scenarios where the underlying data manifold undergoes complex nonlinear transformations. This observation motivates our investigation of gradual adaptation strategies that can better preserve model stability across significant distributional shifts.

Gradual Domain Adaptation (GDA) has emerged as a principled approach to address the fundamental challenge of substantial domain shifts by decomposing the adaptation process into a sequence of intermediate, more manageable steps. The theoretical foundations of GDA were established by [7] and [6] demonstrated that gradual transitions between domains can significantly improve adaptation performance compared to direct source-to-target approaches. This paradigm shift builds upon the key insight that complex real-world domain shifts often evolve gradually rather than occurring abruptly, suggesting that modeling the continuous transformation between domains may better capture the underlying data manifold structure.

Recent advances in GDA have focused on two primary directions: the generation of meaningful intermediate domains and the development of robust adaptation strategies across these domains. Theoretical work by [16] has provided rigorous mathematical frameworks for understanding the benefits of gradual adaptation, while algorithmic innovations have explored various approaches to constructing intermediate distributions. These include gradient flow-based geodesic paths [17] that preserve the intrinsic geometry of the data manifold, style-transfer interpolation techniques [10] that generate visually plausible intermediate samples, and optimal transport methods [9] that minimize the Wasserstein distance between consecutive domains. These methodological advancements collectively represent a significant step forward in addressing large domain gaps, though important challenges remain in scaling these approaches to high-dimensional spaces and ensuring their robustness to noisy or imperfect intermediate domains.

3 Problem Setup

Domain Space Let $\mathcal{Z} = \mathcal{X} \times \mathcal{Y}$ denote the measurable instance space, where $\mathcal{X} \subseteq \mathbb{R}^d$ is the d -dimensional input space and $\mathcal{Y} = \{1, 2, \dots, k\}$ is the label space with k denoting the number of classes.

Gradually Shifting Domain Following the gradual domain shift framework [6], we assume a sequence of $n + 1$ domains $\{\mathcal{D}_t\}_{t=0}^n$ defined over $\mathcal{Z}$. Here, $\mathcal{D}_0$ represents the labeled source domain, $\mathcal{D}_n$ denotes the unlabeled target domain, and the intermediate domains $\mathcal{D}_1, \dots, \mathcal{D}_{n-1}$ form a smooth interpolation between them. Each $\mathcal{D}_t$ corresponds to a distinct data distribution, with the divergence between consecutive domains assumed to be sufficiently small to enable stable adaptation.

Classification and Empirical Risk Minimization The goal of supervised classification is to learn a hypothesis $f : \mathcal{X} \rightarrow \mathcal{Y}$ that minimizes the expected risk under a given distribution $\mathcal{D}_t$. Formally, given a loss function $l : \mathcal{Y} \times \mathcal{Y} \rightarrow \mathbb{R}_{\geq 0}$, the optimal parameters θ are obtained by solving:

$$\theta = \arg \min_{\theta} \mathbb{E}_{(x,y) \sim \mathcal{D}_t} [l(f(x; \theta), y)]. \quad (1)$$

Domain Adaptation In unsupervised domain adaptation (UDA), the model is trained on a labeled source domain $\mathcal{D}_S$ but evaluated on an unlabeled target domain $\mathcal{D}_T$, where $P_S(x) \neq P_T(x)$ while the conditional distribution $P(y | x)$ is assumed to be invariant. The central challenge lies in transferring knowledge across domains despite the distributional shift and the absence of labeled target data.

Gradual Domain Adaptation Gradual domain adaptation (GDA) addresses this challenge by leveraging a sequence of unlabeled intermediate domains $\{\mathcal{D}_t\}_{t=1}^{n-1}$ that bridge $\mathcal{D}_0$ and $\mathcal{D}_n$. Starting

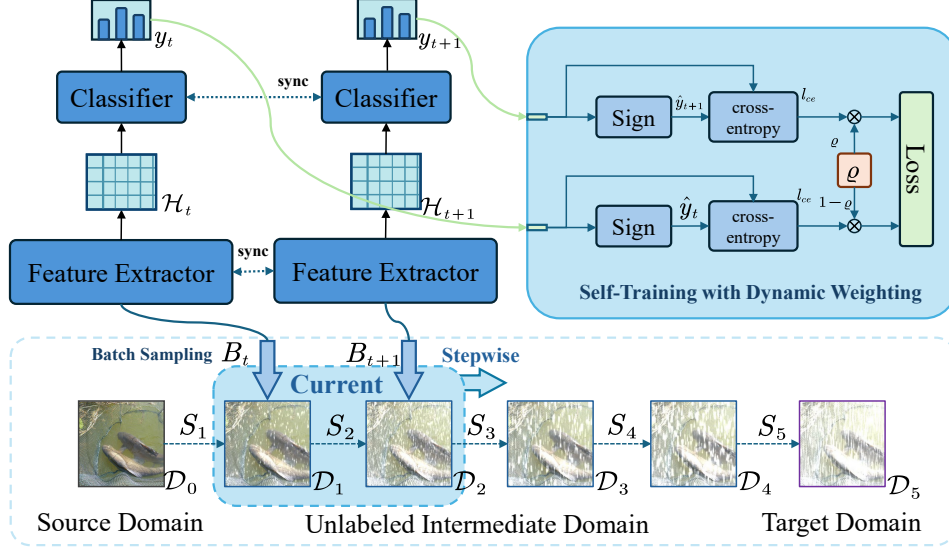


Figure 2: The framework of our *Self-Training with Dynamic Weighting* (STDW). It is designed to facilitate a smooth and controlled adaptation of a model from a source domain to a target domain. The hyperparameter ρ governs the trade-off between the two domains: when $\rho = 0$, the model operates exclusively on the source domain, whereas as ρ increases toward 1, the model progressively shifts its emphasis toward the target domain. Pseudo-labels, generated by the model itself, guide the adaptation process, thereby ensuring a gradual and stable transition across domains.

from a model $f(\cdot; \theta_0)$ trained on the source domain $\mathcal{D}_0$, adaptation proceeds iteratively: at stage $t \in \{1, \dots, n\}$, the current model $f(\cdot; \theta_{t-1})$ generates pseudo-labels for samples from $\mathcal{D}_t$, which are then used to update the model parameters via self-training:

$$\theta_t = \arg \min_{\theta'} \mathbb{E}_{x \sim \mathcal{D}_t} [l(f(x; \theta'), \hat{f}(x; \theta_{t-1}))]. \quad (2)$$

where $\hat{y}(x; \theta_{t-1}) = \arg \max_{y \in \mathcal{Y}} f_y(x; \theta_{t-1})$ denotes the hard pseudo-label assigned by the previous model. The resulting model $f(\cdot; \theta_t)$ is then employed to annotate data from the next domain $\mathcal{D}_{t+1}$. By constraining the distributional shift between consecutive stages to be small, this procedure ensures a controlled and stable propagation of knowledge from source to target, thereby mitigating error accumulation and enhancing generalization in the final target domain.

4 Methodology

This work proposes Self-Training with Dynamic Weighting (STDW), which reconstructs traditional self-training paradigms through a triple adaptive mechanism. Fig. 2 illustrates the overall framework of Self-Training with Dynamic Weighting (STDW).

4.1 Pseudo-labeling Dynamic Learning

Existing gradual domain adaptation (GDA) methodologies typically employ a static pseudo-labeling paradigm, wherein the entire unlabeled dataset $\mathcal{D} = \{x_1, \dots, x_N\}$ is annotated in a single pass. This process involves a classifier $f(\cdot; \theta)$ assigning hard labels through:

$$\hat{f}(x) = \arg \max_y f(x)_y, \quad (3)$$

followed by discarding a fixed proportion (e.g., 10%) of low-confidence samples to mitigate noise [6]. However, residual mislabeling inevitably persists, leading to compounded errors across successive domains and exponential degradation in model accuracy—a phenomenon empirically validated in prior studies.

To address this limitation, we propose *dynamic pseudo-labeling*, a sequential strategy that alternates between incremental pseudo-label generation and classifier refinement. Specifically, we partition

$\mathcal{D}$ into T disjoint mini-batches $\{B_1, \dots, B_T\}$. At iteration t , the model θ_{t-1} labels samples within batch B_t via:

$$\hat{y}_i^{(t)} = \arg \max_y f(x_i; \theta_{t-1})_y \quad \forall x_i \in B_t, \quad (4)$$

yielding pseudo-labels $\{\hat{y}_i^{(t)}\}$. These labels then drive a parameter update by minimizing the cross-entropy loss $\mathcal{L}$ over B_t :

$$\theta_t = \theta_{t-1} - \eta \nabla_{\theta} \mathcal{L} \left(f(B_t; \theta_{t-1}), \{\hat{y}_i^{(t)}\} \right), \quad (5)$$

where η denotes the learning rate. This iterative process is formalized through a batch-wise update operator $\mathcal{U}$:

$$\theta_t = \mathcal{U}(\theta_{t-1}, B_t), \quad t = 1, \dots, T. \quad (6)$$

By progressively refining pseudo-labels with an incrementally improved classifier, our approach circumvents the error accumulation inherent to static labeling schemes. This dynamic interaction between label generation and model adaptation ensures that each batch benefits from the enhanced discriminative capability acquired from preceding batches, thereby alleviating label noise propagation and fostering more stable domain adaptation. The resultant framework demonstrates superior robustness, as evidenced by our experimental analyses.

4.2 Cyclic Batch Matching Across Neighboring Domains

Data comes from a range of domains in the gradual domain adaptation scenario. Consider two neighboring domains $\mathcal{D}_l$ (left domain) and $\mathcal{D}_r$ (right domain), which are partitioned as $\mathcal{D}_l = \{B_{l,1}, B_{l,2}, \dots, B_{l,n}\}$, $\mathcal{D}_r = \{B_{r,1}, B_{r,2}, \dots, B_{r,m}\}$.

To facilitate robust inter-domain adaptation, we define cyclic sequences that allow batches from each domain to be matched in a fixed, periodic manner. Specifically, we define the sequences $\{B_l(t)\}_{t \geq 0}$ and $\{B_r(t)\}_{t \geq 0}$, with the mapping given by:

$$B_l(t) = B_{l,i(t)}, \quad B_r(t) = B_{r,j(t)}, \quad (7)$$

where the indexing functions $i(t)$ and $j(t)$ are defined as:

$$\begin{aligned} i(t) &= (t \bmod n) + 1, \\ j(t) &= \left(\left(t + \left\lfloor \frac{t}{n} \right\rfloor \right) \bmod m \right) + 1. \end{aligned} \quad (8)$$

This formulation ensures the batches are sampled cyclically over the two domains. The resulting cyclic matching can then be represented by the ordered pair sequence:

$$\left\{ \left(B_{l,i(k)}, B_{r,j(k)} \right) \right\}_{k \geq 0}. \quad (9)$$

Consider a sequence of $n+1$ domains $\{\mathcal{D}_t\}_{t=0}^n$, where each domain $\mathcal{D}_t$ consists of m data batches denoted by $\{B_{t,1}, B_{t,2}, \dots, B_{t,m(t)}\}$. We define a time-varying classifier $f^{(t,k)}$ to be the model after the k -th batch update within domain $\mathcal{D}_{t-1}$ and $\mathcal{D}_t$. Its evolution is governed by the incremental update rule:

$$\theta^{(t,k+1)} = \Phi(\theta^{(t,k)}, B_{t-1,i(k)}, B_{t,j(k)}), \quad (10)$$

where Φ is an optimization operator defined via the following objective:

$$\Phi = \arg \min_{\theta'} \left\{ \mathbb{E}_{x \sim B_{t,i(k)}} \left[\ell_{\text{ce}} \left(f(x_i; \theta'), \hat{f}(x; \theta) \right) \right] + \mathbb{E}_{x \sim B_{t,j(k)}} \left[\ell_{\text{ce}} \left(f(x_i; \theta'), \hat{f}(x; \theta) \right) \right] \right\}, \quad (11)$$

Just like Eq. 5 and Eq. 6, we can update θ through Φ .

4.3 Stepwise Dynamic Osmosis

We formulate the cross-domain adaptation process as the following optimization problem:

$$\theta^{(t,k+1)} = \Phi(\theta^{(t,k)}, B_{t-1,i(k)}, B_{t,j(k)}, \varrho), \quad (12)$$

$$\Phi = \arg \min_{\theta'} \left\{ (1-\varrho) \mathbb{E}_{x \sim B_{t,i(k)}} \left[\ell_{\text{ce}}(f(x_i; \theta'), \hat{f}(x; \theta)) \right] + \varrho \mathbb{E}_{x \sim B_{t,j(k)}} \left[\ell_{\text{ce}}(f(x_i; \theta'), \hat{f}(x; \theta)) \right] \right\}. \quad (13)$$

where $\varrho \in [0, 1]$ is a hyperparameter that balances the contribution of the current domain $\mathcal{D}_i$ and the subsequent domain $\mathcal{D}_{i+1}$. As the training progresses, ϱ increases from 0 to 1, thereby gradually migrating the learned knowledge from the source domain $\mathcal{D}_i$ to the target domain $\mathcal{D}_{i+1}$.

Algorithm 1 Self-Training with Dynamic Weighting (STDW)

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1: Input: Source batches  $\{B_{0,k}\}_{k=1}^m$ , domain sequence  $\{\mathcal{D}_t\}_{t=1}^n$ , initial model  $f^{(0,0)}$ , Inter-domain
   migration steps:  $s$ 
2: Output: Adapted model  $f^{(n,m)}$ 
3:  $g \leftarrow 1/s$ 
4: for  $t = 1$  TO  $n$  do
5:   while  $\varrho \leq 1$  do
6:     for  $k = 1$  TO  $m \cdot \text{epochs}$  do
7:       Fetch batch  $B_{t,k}$ , generate pseudo-labels:  $\hat{y} \leftarrow \hat{f}(x; \theta^{(t,k-1)})$ 
8:       Use Eq. 12, Eq. 13 update model:  $\theta^{(t,k)} \leftarrow \Phi(\theta^{(t,k-1)}, B_{t-1,i(k)}, B_{t,j(k)}, \varrho)$ 
9:     end for
10:     $\varrho \leftarrow \varrho + g$ 
11:   end while
12:   Switch to the next domain:  $\theta^{(t+1,0)} \leftarrow \theta^{(t,m)}$ 
13: end for

```

5 Experiments

5.1 Environments Setup

Datasets. Following established gradual domain adaptation protocols [6, 9], we utilize four core datasets: Rotated MNIST [18] and Color-Shift MNIST for controlled synthetic transformations, Portraits Dataset [19] for real-world temporal shifts, and Cover Type Dataset [20] for tabular domain adaptation. The Rotated MNIST dataset, derived from the standard MNIST digits [18], introduces a progressive geometric transformation where source images (0° rotation) gradually evolve to target images (45° rotation) through intermediate domains of increasing rotation angles [9]. Similarly, Color-Shift MNIST examines photometric transformations by systematically varying pixel intensity ranges from [0,1] in the source domain to [1,2] in the target domain [9]. For real-world evaluation, the Portraits Dataset [19] provides a temporal domain shift spanning over a century (1905-2013), partitioned into nine chronological domains with distinct fashion and photographic characteristics [6]. The Cover Type Dataset [20] offers a challenging tabular scenario where domains are constructed based on ecological proximity to water sources [6]. To further stress-test our method under severe distribution shifts, we incorporate two additional corruption benchmarks: CIFAR-10-C and CIFAR-100-C [21], which systematically apply 15 types of image corruptions at varying severity levels, treating the highest severity as the target domain.

Implementation. For image datasets (Rotated MNIST, Color-Shift MNIST, Portraits), we implement a convolutional neural network comprising three 32-channel convolutional layers followed by two 256-unit fully connected layers. The tabular Cover Type dataset utilizes a progressively expanding fully connected architecture (128-256-512 units). All models incorporate ReLU activations, batch normalization [22], and dropout regularization [23], optimized using Adam [24] with carefully tuned hyperparameters. The transport network architecture features residual-connected generators and three-layer discriminators (128 hidden units per layer) to facilitate domain transitions. Our evaluation systematically varies the number of intermediate domains (0-4) to analyze adaptation trajectory smoothness. For the corruption benchmarks, we employ established robust architectures: WideResNet-28 [25] for CIFAR-10-C and ResNeXt-29 [26] for CIFAR-100-C, following Robust-Bench protocols [27, 28] to ensure comparable evaluation conditions. All experiments are conducted on NVIDIA RTX 4090 GPUs with identical random seeds for reproducibility.

Benchmarks. Our comparative analysis encompasses the following state-of-the-art domain adaptation methods spanning both conventional and gradual adaptation paradigms. The evaluation includes three unsupervised domain adaptation baselines: DANN [29] (adversarial adaptation), DeepCoral [30] (correlation alignment), and DeepJDOT [31] (joint distribution optimal transport). For gradual domain adaptation, we benchmark against five recent approaches: GST [6] (gradual self-training), IDOL [8] (intermediate domain learning), GOAT [9] (geodesic optimal transport), GGF [17] (gradual geometric flow), and GNF [32] (gradual normalizing flows). To evaluate the adaptability of the model in a slowly evolving environment, we conducted experiments using TTA application methods including TENT-continual [33], AdaContrast [34], CoTTA [35], GTTA-MIX [36] and the GDA method GST. In all the experiments, we took the error rate as the main indicator in order to make a direct comparison with the existing literature and provide a clear explanation of the model performance under different adaptation challenges at the same time.

5.2 Results

Table 1 presents a comprehensive comparison of our method against state-of-the-art unsupervised domain adaptation (UDA) and gradual domain adaptation (GDA) approaches across multiple benchmark datasets. Our *Self-Training with Dynamic Weighting* (STDW) consistently achieves the best performance, establishing new state-of-the-art results with substantial margins. Specifically, STDW improves absolute accuracy by **11.2%**, **6.5%**, **0.94%**, and **4.3%** over the second-best methods. These gains underscore the effectiveness of STDW in modeling continuous distributional shifts through its dynamic weighting mechanism, in contrast to static alignment strategies (e.g., DANN) or single-step gradual adaptation schemes. Moreover, among the limited set of domain adaptation frameworks capable of operating across diverse adaptation scenarios—including both abrupt and gradual shifts—STDW demonstrates exceptional versatility and robustness, highlighting its broad applicability.

Table 1: Benchmarks Comparison on different datasets, including UDA methods and GDA methods.

UDA/GDA methods	Rotated MNIST	Color-Shift MNIST	Portraits	Cover Type
DANN [37]	44.2	56.5	73.8	65.2
DeepCoral [30]	49.6	63.5	71.9	66.8
DeepJDOT [31]	51.6	65.8	72.5	67.4
GST [6]	83.8	74.0	82.6	73.5
IDOL [8]	87.5	78.3	85.5	72.1
GOAT [9]	86.4	91.8	83.6	69.9
GGF [17]	67.72	73.6	86.1	71.2
CNF [38]	62.55	70.4	84.6	70.8
STDW (Ours)	97.6	98.3	87.1	74.2

The experimental results presented in Table 3 demonstrate the effectiveness of our proposed STDW method compared to seven state-of-the-art approaches across 15 distinct corruption types at severity level 5 achieving superior performance overall, attaining the lowest mean error rate of 15.5% on CIFAR-10-C and 25.8% on CIFAR-100-C. This represents a significant improvement over the source-only baseline (43.5% and 46.4% respectively) and outperforms all comparison methods, including the closest competitor GTTA-MIX (15.6% and 28.9%). Notably, STDW achieves the best performance on 11 out of 15 corruption types for CIFAR-10-C and 14 out of 15 for CIFAR-100-C, demonstrating remarkable consistency across diverse corruption patterns.

Furthermore, for high-frequency corruptions like Gaussian noise, shot noise, and impulse noise, STDW shows particularly strong performance with error rate reductions of 3.3-11.6 percentage points compared to the next best method. This suggests our approach effectively handles high-frequency distortions that typically challenge conventional adaptation methods. For geometric distortions (e.g., zoom, motion) and weather-based corruptions (e.g., snow, frost), STDW maintains consistent advantages, indicating robust performance across both spatial and photometric transformations. The consistent superiority of STDW across both datasets and corruption types validates our key contributions: (1) the effectiveness of progressive domain transport through weighted intermediate steps, and (2) the robustness of our approach to diverse types of domain shifts.

Table 2: Classification error rate (%) on the highest damage severity level 5 after gradual adaptation of CIFAR100-to-CIFAR100C with progressively higher damage. For all method results evaluated on the same ResNeXt-29 that has been trained on the source domain, for STDW we fixed the use of 2 intermediate steps. We report the average performance of our method over 5 runs. **Red** indicates the best value, **Green** indicates the second-best.

Methods		Source only	BN-1	TENT-cont.	AdaContrast	CoTTA	GTТА-MIX	GST	STDW (ours)
Gradual		X	X	X	X	X	X	✓	✓
CIFAR-10-C	Gaussian	72.3	28.1	24.8	29.1	24.3	23.4	50.0	21.5
	Shot	65.7	26.1	20.6	22.5	21.3	18.3	43.9	19.0
	Impulse	72.9	36.3	28.6	30.0	26.6	25.5	50.3	27.9
	Defocus	46.9	12.8	14.4	14.0	11.6	10.1	20.6	9.6
	Glass	54.3	35.3	31.1	32.7	27.6	27.3	51.2	28.3
	Motion	34.8	14.2	16.5	14.1	12.2	11.6	17.2	10.3
	Zoom	42.0	12.1	14.1	12.0	10.3	10.1	16.7	8.5
	Snow	25.1	17.3	19.1	16.6	14.8	14.1	17.5	3.0
	Frost	41.3	17.4	18.6	14.9	14.1	13.0	24.3	13.3
	Fog	26.0	15.3	18.6	14.4	12.4	10.9	17.5	11.7
	Bright	9.3	8.4	12.2	8.1	7.5	7.4	6.9	7.1
	Contrast	46.7	12.6	20.3	10.0	10.6	9.0	13.2	8.8
	Elastic	26.6	23.8	25.7	21.9	18.3	19.4	24.9	19.6
	Pixelate	58.5	19.7	20.8	17.7	13.4	14.5	39.9	13.4
JPEG	30.3	27.3	24.9	20.0	17.3	19.8	26.6	20.1	
Mean	43.5	20.4	20.7	18.5	16.2	15.6	28.1	15.5	
CIFAR-100-C	Gaussian	73.0	42.1	37.2	42.3	40.1	36.4	49.8	31.0
	Shot	68.0	40.7	35.8	36.8	37.7	32.1	56.7	27.6
	Impulse	39.4	42.7	41.7	38.6	39.7	34.0	32.3	26.1
	Defocus	29.3	27.6	37.9	27.7	26.9	24.4	22.5	22.1
	Glass	54.1	41.9	51.2	40.1	38.0	35.2	41.6	31.6
	Motion	30.8	29.7	48.3	29.1	27.9	25.9	25.0	22.9
	Zoom	28.8	27.9	48.5	27.5	26.4	23.9	23.3	22.6
	Snow	39.5	34.9	58.4	32.9	32.8	28.9	30.3	25.0
	Frost	45.8	35.0	63.7	30.7	31.8	27.5	32.2	25.4
	Fog	50.3	41.5	71.1	38.2	40.3	30.9	38.1	25.8
	Bright	29.5	26.5	70.4	25.9	24.7	22.6	22.1	21.9
	Contrast	55.1	30.3	82.3	28.3	26.9	23.4	27.0	24.3
	Elastic	37.2	35.7	88.0	33.9	32.5	29.4	33.1	27.2
	Pixelate	74.7	32.9	88.5	33.3	28.3	25.5	40.8	22.9
	JPEG	41.2	41.2	90.4	36.2	33.5	33.3	35.8	30.0
Mean	46.4	35.4	60.9	33.4	32.5	28.9	33.3	25.8	

Table 3: Comparison of accuracy for our STDW method across various datasets, considering different numbers of given intermediate domains (including the source and target domains). Results are averaged over 5 runs, with error bars representing the 95% confidence interval of the mean.

Rotated MNIST						Color-Shift MNIST					
# Given Domains	# Inter-domain counts in STDW					# Inter-domain counts in STDW					
	0	1	2	3	4	0	1	2	3	4	
2	81.5±1.3	82.8±3.5	81.7±4.4	82.0±6.4	83.6±1.2	86.2±0.1	96.5±0.0	87.2±3.6	86.6±0.0	86.6±0.1	
3	95.9±0.4	96.5±0.8	96.8±0.3	96.9±0.1	96.8±0.1	98.1±0.0	98.2±0.0	98.2±0.0	98.3±0.0	98.3±0.0	
4	96.5±0.2	96.9±0.1	96.8±0.0	96.8±0.0	96.8±0.1	98.3±0.0	98.3±0.0	98.3±0.0	98.3±0.0	98.3±0.0	
5	96.8±0.1	96.9±0.1	96.7±0.1	96.9±0.0	97.0±0.1	98.3±0.0	98.3±0.0	98.3±0.0	98.2±0.0	98.3±0.0	
6	96.9±0.1	96.9±0.1	96.9±0.1	97.6±0.0	96.9±0.0	98.3±0.0	98.3±0.0	98.3±0.0	98.2±0.0	98.2±0.0	
Portraits						Cover Type					
# Given Domains	# Inter-domain counts in STDW					# Inter-domain counts in STDW					
	0	1	2	3	4	0	1	2	3	4	
2	83.7±0.3	84.4±0.8	85.1±0.6	85.1±0.8	85.1±0.5	69.7±0.0	70.0±0.0	70.5±0.1	71.2±0.0	71.8±0.1	
3	84.1±0.3	84.6±0.2	84.8±0.5	84.7±0.1	84.7±0.2	70.1±0.0	72.3±0.0	73.9±0.0	74.3±0.0	74.4±0.1	
4	83.8±0.7	84.0±0.1	84.0±0.2	83.8±0.3	83.9±0.1	71.5±0.0	73.8±0.0	74.2±0.0	74.0±0.0	74.2±0.0	
5	84.8±0.4	84.8±0.4	84.8±0.4	84.8±0.2	84.9±0.4	72.5±0.1	74.2±0.0	74.1±0.0	74.2±0.1	73.9±0.0	
6	85.3±0.9	86.1±0.4	85.8±1.0	85.6±1.8	85.4±0.9	73.1±0.0	74.1±0.0	73.4±0.0	73.9±0.0	73.4±0.0	

We present a comparative evaluation of the proposed STDW framework across four benchmark datasets: *Rotated MNIST*, *Color-Shift MNIST*, *Portraits*, and *Cover Type*, with detailed results provided in Table 3. For each dataset, experiments were repeated multiple times under identical conditions, and the reported metrics represent the mean performance together with their associated variance intervals (e.g., $\pm$ one standard deviation). The leftmost column in each table corresponds to the baseline obtained via adversarial training alone—specifically, a domain-adversarial setup without the integration of flow matching—serving as a reference point to quantify the contribution of our proposed components.

The experimental results demonstrate the effectiveness of the STDW framework across the four benchmark datasets. For each dataset, we systematically vary two key factors: (i) the total number of available domains (including the source and target), and (ii) the number of inter-domain adaptation steps employed in the STDW procedure. We evaluate model performance as the number of adaptation steps increases, thereby providing a fine-grained analysis of how the granularity of domain interpolation influences the overall efficacy of the adaptation process. Notably, the observed standard deviations across five independent runs remain consistently low (all $\leq 1.2\%$), underscoring the stability and reliability of our method under diverse domain configurations.

5.3 Ablation Study

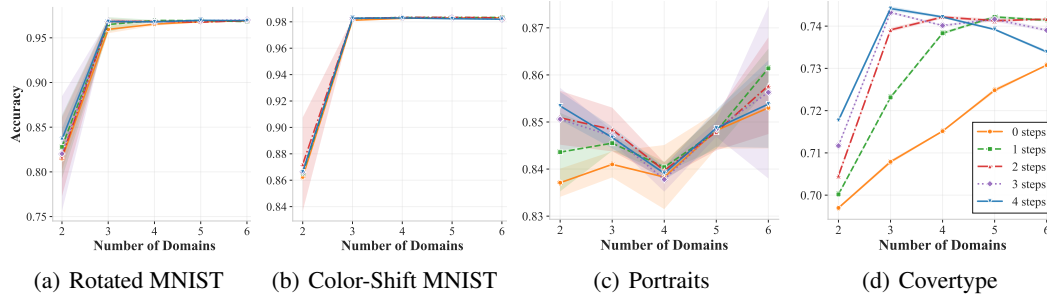


Figure 3: Ablation of STDW under different domain configurations and step counts. Accuracy on four benchmarks when varying the total number of domains (x-axis) and the inter-domain step counts used by STDW (curves). Each curve labeled “0–4 steps” indicates how many stepwise dynamic osmosis updates are performed per adjacent domain pair.

To investigate the impact of intermediate domains on adaptation performance, we conduct ablation studies on four benchmark datasets under a non-STDW baseline, varying the number of domains from 2 (i.e., source and target only) to 6 (i.e., source, target, and four unlabeled intermediate domains). The results, summarized in Figure 3, reveal a consistent trend: the inclusion of intermediate domains leads to substantial improvements in classification accuracy across most settings, accompanied by a notable reduction in standard deviation (computed over multiple runs). These findings strongly support the hypothesis that gradual, stepwise domain adaptation—enabled by intermediate distributions—plays a pivotal role in enhancing both the effectiveness and stability of domain generalization, particularly under significant source–target shifts.

Table 4: Comparison of STDW Method (Ours) with baselines across different domain adaptation steps on Rotated MNIST and Portraits datasets.

Method	Rotated MNIST					Portraits				
	0	1	2	3	4	0	1	2	3	4
Ours	83.3 $\pm$ 0.9	85.0 $\pm$ 0.5	86.1 $\pm$ 0.4	86.9 $\pm$ 0.2	88.1 $\pm$ 1.5	82.9 $\pm$ 1.2	84.6 $\pm$ 0.2	85.0 $\pm$ 0.9	85.1 $\pm$ 0.2	85.3 $\pm$ 0.1
Sorted	84.1 $\pm$ 0.8	86.4 $\pm$ 0.6	86.0 $\pm$ 1.7	86.3 $\pm$ 0.1	85.7 $\pm$ 0.5	82.7 $\pm$ 0.5	84.0 $\pm$ 0.6	84.2 $\pm$ 0.1	84.3 $\pm$ 0.2	84.5 $\pm$ 0.1
Rand	83.4 $\pm$ 0.2	80.9 $\pm$ 7.0	84.5 $\pm$ 2.8	86.3 $\pm$ 0.9	86.1 $\pm$ 0.4	82.4 $\pm$ 0.5	84.0 $\pm$ 0.6	84.2 $\pm$ 0.2	84.3 $\pm$ 0.2	84.1 $\pm$ 0.1
Fixed	83.3 $\pm$ 0.0	83.7 $\pm$ 0.0	83.8 $\pm$ 0.1	83.8 $\pm$ 0.1	84.1 $\pm$ 0.0	83.9 $\pm$ 0.3	83.4 $\pm$ 0.0	83.1 $\pm$ 2.1	84.1 $\pm$ 0.1	84.7 $\pm$ 0.3

Additionally, we compare our stepwise dynamic osmosis strategy—referred to as *Ours (Equal)*, which linearly increases the weighting hyperparameter ϱ in equal increments across adaptation steps—against three representative baselines: *Fixed* ($\varrho = 0.5$ held constant), *Rand* (ϱ sampled independently from a uniform distribution $\mathcal{U}(0, 1)$ at each step), and *Sorted* (a variant of *Rand* where

sampled ϱ values are sorted in ascending order to enforce monotonicity). Experiments are conducted on the *Rotated MNIST* and *Portraits* datasets under a two-domain setting (source and target only), with the number of inter-domain adaptation steps varied from 0 to 4. Results, reported in Table 4, show that *Equal* consistently achieves the highest final accuracy—for instance, attaining 88.1% on *Rotated MNIST* at Step 4, compared to 84.1% and 86.1% for *Fixed* and *Rand*, respectively. Moreover, *Equal* exhibits significantly lower variance across runs (e.g., ± 1.5 vs. ± 7.0 at Step 1 on *Rotated MNIST*), highlighting its superior stability. These results demonstrate that a controlled, monotonic increase of ϱ —as opposed to static, random, or even sorted-random schedules—yields more reliable and optimal adaptation performance.

6 Conclusion

This paper presents Self-Training with Dynamic Weighting (STDW), an innovative approach to Gradual Domain Adaptation (GDA) that systematically addresses the fundamental challenge of smooth knowledge migration across evolving domains. The proposed methodology introduces a dynamic weighting mechanism governed by the hyperparameter ϱ , which continuously modulates the relative influence between source and target domains throughout the adaptation process. This dynamic balancing enables a progressive and efficient knowledge migration within the self-training framework, effectively mitigating domain bias while maintaining model stability. Comprehensive experimental validation across multiple benchmark datasets confirms that STDW achieves superior performance compared to existing state-of-the-art methods, demonstrating significant improvements in both classification accuracy and model robustness under varying domain shift conditions.

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Limitations

While the proposed STDW method demonstrates significant improvements in gradual domain adaptation, several limitations should be acknowledged. First, the performance of STDW relies heavily on the availability and quality of intermediate domains, which may not always be accessible or well-defined in real-world scenarios. Second, the dynamic weighting mechanism, though effective, introduces additional hyperparameters (e.g., the scheduling of ϱ) that require careful tuning, potentially increasing the computational overhead during training. Third, the method assumes a smooth transition between domains, which might not hold for highly discontinuous or abrupt domain shifts. Additionally, the current experiments focus primarily on image and tabular data, leaving its applicability to other data modalities (e.g., text or time-series) unexplored. Finally, the theoretical analysis, while rigorous, relies on assumptions such as bounded Wasserstein distances and Lipschitz continuity, which may not fully capture the complexity of all practical domain adaptation problems. These limitations highlight directions for future work, such as automating hyperparameter selection and extending the framework to handle more diverse and challenging domain shifts.

A Supplementary Experimental Results

Classification correctness (%) for the CIFAR10-to-CIFAR-10-C, CIFAR100-to-CIFAR-100-C, and ImageNet-to-ImageNet-C adaptation task on the highest corruption severity level 5. For CIFAR-10-C the results are evaluated on WideResNet-28, for CIFAR-100-C on ResNeXt-29, and for ImageNet-C, ResNet-50 is used.

Table 5: Classification correctness (%) on the highest damage severity level 5 after gradual adaptation of CIFAR10-to-CIFAR10C with progressively higher damage. For all method results evaluated on the same WideResNet-28 that has been trained on the source domain, for STDW we fixed the use of 2 intermediate steps. We report the average performance of our method over 5 runs.

Method	# Given Domains	<i>gaussian</i>	<i>shot</i>	<i>impulse</i>	<i>defocus</i>	<i>glass</i>	<i>motion</i>	<i>zoom</i>	<i>snow</i>	<i>frost</i>	<i>fog</i>	<i>brightness</i>	<i>contrast</i>	<i>elastic</i>	<i>pixelate</i>	<i>jpeg</i>	Mean
Source	-	27.7	34.3	27.1	53.1	45.7	65.2	58.0	74.9	58.7	74.0	90.7	53.3	73.4	41.5	69.7	56.5
GST	2	37.0	40.9	33.8	57.5	46.3	67.1	58.8	76.7	60.6	76.9	91.9	60.6	74.1	44.8	70.5	59.8
	3	38.3	44.0	39.1	73.8	46.5	70.1	68.1	80.2	65.1	79.4	92.6	80.4	71.5	46.4	71.2	64.5
	4	41.4	48.7	41.5	76.2	48.2	76.8	75.7	80.0	71.8	81.5	93.0	85.4	75.0	51.9	72.1	68.0
	5	42.5	50.3	45.2	79.2	49.1	78.0	78.5	80.4	72.2	82.0	93.1	86.1	75.0	54.1	73.1	69.2
	6	50.0	56.1	49.7	79.4	48.8	82.8	83.3	82.5	75.7	82.5	93.1	86.8	75.1	60.1	73.4	71.9
	6	50.0	56.1	49.7	79.4	48.8	82.8	83.3	82.5	75.7	82.5	93.1	86.8	75.1	60.1	73.4	71.9
GOAT	2	27.7	34.3	27.1	53.1	45.8	65.3	58.1	74.9	58.7	74.0	90.7	53.4	73.5	41.6	69.8	56.5
	3	27.5	34.3	27.0	53.2	45.8	65.4	58.2	74.9	58.8	74.0	90.7	53.5	73.4	41.7	69.8	56.5
	4	27.4	34.2	26.9	53.2	45.6	58.2	65.4	75.0	59.0	74.0	90.6	53.4	73.6	41.8	69.8	56.5
	5	27.3	34.2	26.9	53.3	45.6	65.5	58.4	75.1	59.0	74.0	90.7	53.4	73.6	41.8	69.8	56.6
	6	27.3	34.3	27.0	53.3	45.5	65.7	58.5	75.1	59.0	74.0	90.7	53.4	73.6	41.9	69.8	56.6
	6	27.3	34.3	27.0	53.3	45.5	65.7	58.5	75.1	59.0	74.0	90.7	53.4	73.6	41.9	69.8	56.6
STDW (Ours)	2	73.6	75.5	65.4	88.5	66.4	87.5	89.2	84.0	83.5	86.2	92.5	88.8	77.9	82.2	74.0	81.0
	3	75.0	77.0	68.3	89.5	69.2	88.5	90.7	85.2	84.7	87.5	92.9	90.3	79.1	83.9	76.4	82.5
	4	76.4	80.0	69.6	90.0	69.7	88.9	91.4	86.1	85.6	88.2	92.9	90.9	79.7	85.2	77.5	83.5
	5	77.2	80.0	70.9	90.4	70.9	89.4	91.5	86.6	86.3	88.3	92.8	91.2	80.1	86.2	78.7	84.0
	6	78.5	81.0	72.1	90.4	71.7	89.7	91.4	97.0	86.7	88.3	92.7	90.8	80.4	86.6	79.9	84.5
	6	78.5	81.0	72.1	90.4	71.7	89.7	91.4	97.0	86.7	88.3	92.7	90.8	80.4	86.6	79.9	84.5

B Theoretical Arguments

B.1 Lyapunov Stability Under Cyclic Matching and Switching Anchors

For completeness, we extend the stability argument to the piecewise-smooth path constructed for discontinuous shifts. Let θ_t denote the parameters at step t and consider the mixed loss on a matched pair of mini-batches

$$L_d(\theta_t) = \varrho_t \ell(\theta_t, \mathcal{B}_t^{(d)}) + (1 - \varrho_t) \ell(\theta_t, \mathcal{B}_t^{(d-1)}), \quad (14)$$

Table 6: Classification correctness (%) on the highest damage severity level 5 after gradual adaptation of CIFAR100-to-CIFAR100C with progressively higher damage. For all method results evaluated on the same ResNeXt-29 that has been trained on the source domain, for STDW we fixed the use of 2 intermediate steps. We report the average performance of our method over 5 runs.

Method	# Given Domains	gaussian	shot	impulse	defocus	glass	motion	zoom	snow	frost	fog	brightness	contrast	elastic	pixelate	jpeg	Mean
Source	-	27.0	12.0	60.6	70.7	45.9	69.2	71.2	60.5	54.2	49.7	70.5	44.9	62.8	25.3	58.8	53.6
GST	2	49.4	52.3	62.4	72.4	51.9	70.4	72.6	64.7	63.0	56.5	73.7	61.0	64.0	50.2	60.0	61.6
	3	48.3	50.4	62.8	74.2	54.7	71.8	74.4	66.6	63.8	57.4	74.9	64.0	64.1	49.4	61.1	62.5
	4	47.7	49.5	64.2	75.6	56.1	73.0	75.7	67.3	65.6	59.1	76.5	67.2	65.5	50.3	61.9	63.7
	5	50.0	52.0	66.2	76.6	57.9	73.8	76.2	68.1	66.8	60.3	77.2	69.1	66.5	53.7	63.4	65.2
	6	50.2	53.3	67.7	77.5	58.6	75.0	76.7	69.7	67.8	61.9	77.9	73.0	66.9	59.2	64.2	66.7
GOAT	2	27.1	32.0	60.8	70.9	45.9	69.3	71.3	60.6	54.2	49.9	70.4	44.9	63.0	25.0	58.8	53.6
	3	26.8	31.9	60.7	71.0	45.9	69.6	71.3	60.6	54.2	49.8	70.4	45.1	63.1	25.2	58.7	53.6
	4	26.8	32.0	60.9	71.1	45.9	69.6	71.2	60.5	54.4	50.0	70.5	45.5	63.0	25.2	58.8	53.7
	5	26.3	32.1	60.9	71.1	46.0	69.7	71.3	60.6	54.3	50.0	70.6	45.9	63.2	25.2	58.6	53.7
	6	26.6	32.1	60.9	71.3	46.2	69.8	71.2	60.7	54.3	50.0	70.6	46.3	63.2	25.7	58.8	53.8
STDW (Ours)	2	61.5	63.9	60.7	75.4	61.3	73.1	75.3	69.3	68.1	62.4	76.4	72.2	67.6	71.2	62.0	68.0
	3	64.0	67.6	64.4	77.1	65.0	74.8	76.9	71.0	70.0	65.5	77.7	74.7	70.1	74.1	64.5	70.5
	4	65.6	69.0	67.6	77.7	66.0	76.1	77.3	72.3	71.6	68.7	78.1	75.5	70.9	76.0	66.4	71.9
	5	66.8	70.5	70.9	77.9	67.6	76.1	77.4	73.1	72.4	71.6	78.0	75.4	72.3	76.4	67.5	72.9
	6	69.0	72.4	73.9	77.8	68.4	77.1	77.3	75.0	74.6	74.2	78.1	75.7	72.8	77.1	70.0	74.2

where ℓ is cross-entropy and $\varrho_t \in [0, 1]$. Assume ℓ is L -smooth and μ -strongly convex in a neighbourhood of the local joint minimizer θ_d^* for the pair (D_{d-1}, D_d) . With gradient descent

$$\theta_{t+1} = \theta_t - \eta \nabla L_d(\theta_t) \quad (15)$$

and step size $\eta \in (0, 2/L)$, define the Lyapunov function

$$V_d(\theta) = \frac{1}{2} |\theta - \theta_d^*|^2 \quad (16)$$

Standard smooth strongly-convex analysis yields

$$V_d(\theta_{t+1}) \leq V_d(\theta_t) - \eta \left(\mu - \frac{L\eta}{2} \right) |\theta_t - \theta_d^*|^2, \quad (17)$$

so V_d strictly decreases whenever $\theta_t \neq \theta_d^*$ and $\eta < 2\mu/L^2$. Cyclic matching enumerates all batch pairs once per epoch without changing smoothness or curvature, so the decrease persists across iterations. For a discontinuous path approximated by anchors $A_0, \dots, A_q$ we obtain a switched system with modes $d \in \{1, \dots, q\}$. If there exists a common quadratic Lyapunov function $V(\theta) = \frac{1}{2} |\theta - \theta^*|^2$ valid in the union of neighbourhoods of θ_d^* —for instance when $|\theta_d^* - \bar{\theta}^*|$ is bounded and the Hessians share eigenvalue bounds (μ, L) —then the same inequality holds for all modes with the same η , ensuring global asymptotic stability under arbitrary switching. When a common Lyapunov function is too conservative, we adopt a dwell-time condition implemented by the discrepancy-aware controller: the mode can switch (i.e., we advance ϱ or move to the next anchor) only after the gradient norm on the current mode falls below a tolerance and the consistency gates are met. In both cases, the energy decreases monotonically, preventing divergence even under abrupt transitions.

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